



## Applications of Self Organizing Maps in Wind Energy Meteorology

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*Published in:*  
Proceedings

*Publication date:*  
2010

*Document Version*  
Publisher's PDF, also known as Version of record

[Link back to DTU Orbit](#)

*Citation (APA):*  
Hahmann, A. N., Vincent, C. L., & Kelly, M. C. (2010). Applications of Self Organizing Maps in Wind Energy Meteorology. In *Proceedings*

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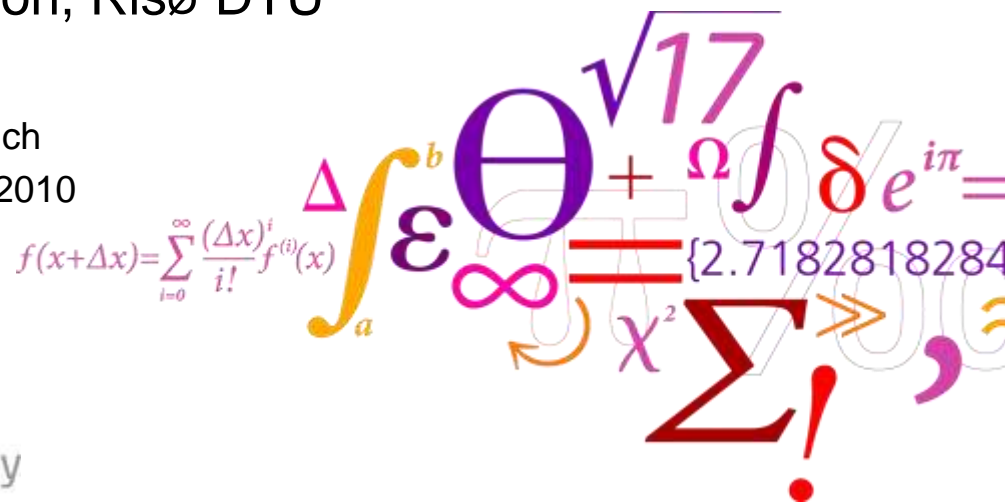
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# Applications of Self Organizing Maps in Wind Energy Meteorology

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September 2010



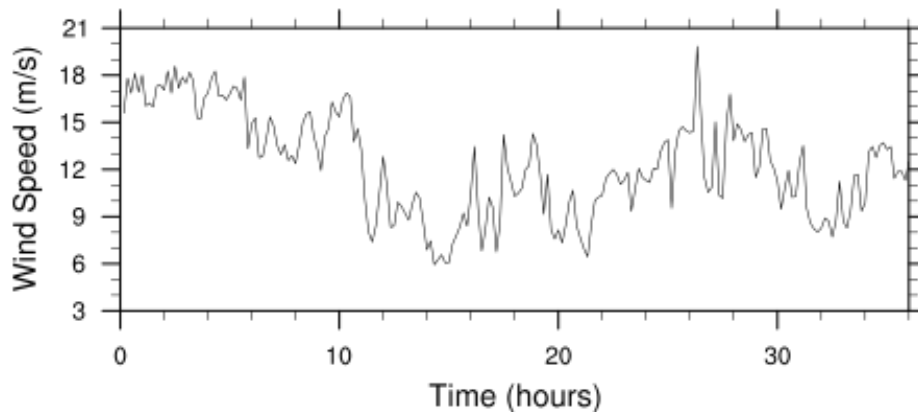
$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$

# Two examples

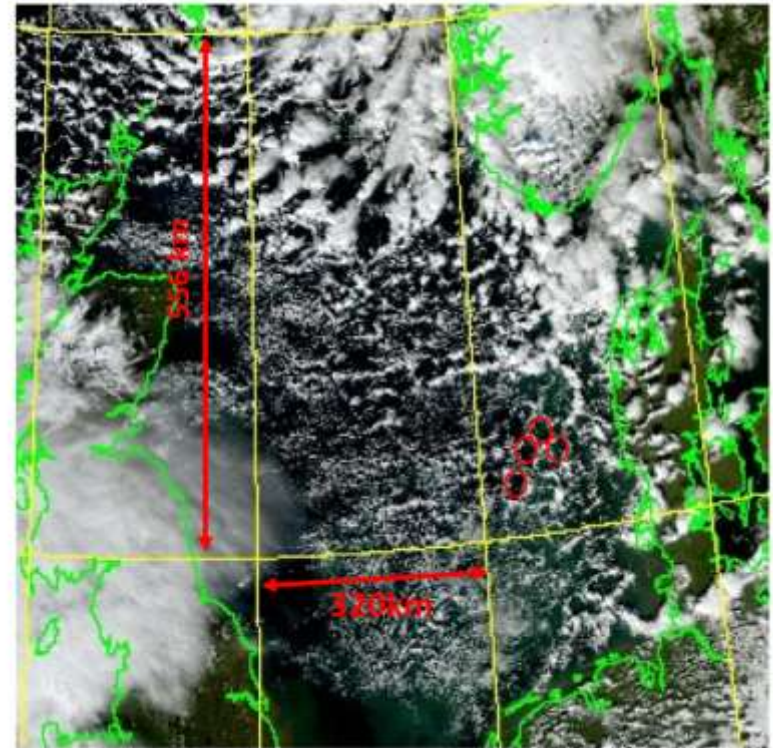
- Statistical forecasting of severe wind variability events
  - Synoptic classification using self organizing maps
  - 20 years of ERA interim reanalysis MSLP data
  - Comparison with satellite pictures, Horns Rev met mast and WasP wind classes
- Generation of mesoscale wind atlas
  - Synoptic classification used to select a representative sample of large-scale wind forcing
  - The mesoscale downscaling from each of these “forcings” is then scaled according with the frequency of occurrence
  - How many samples from each node are needed?

# Meteorological conditions that generate high-frequency variations in wind speed

Observed time series of wind speed at Horns Rev



Test the relationship between the large scale flow and the locally observed wind variability at Horns Rev

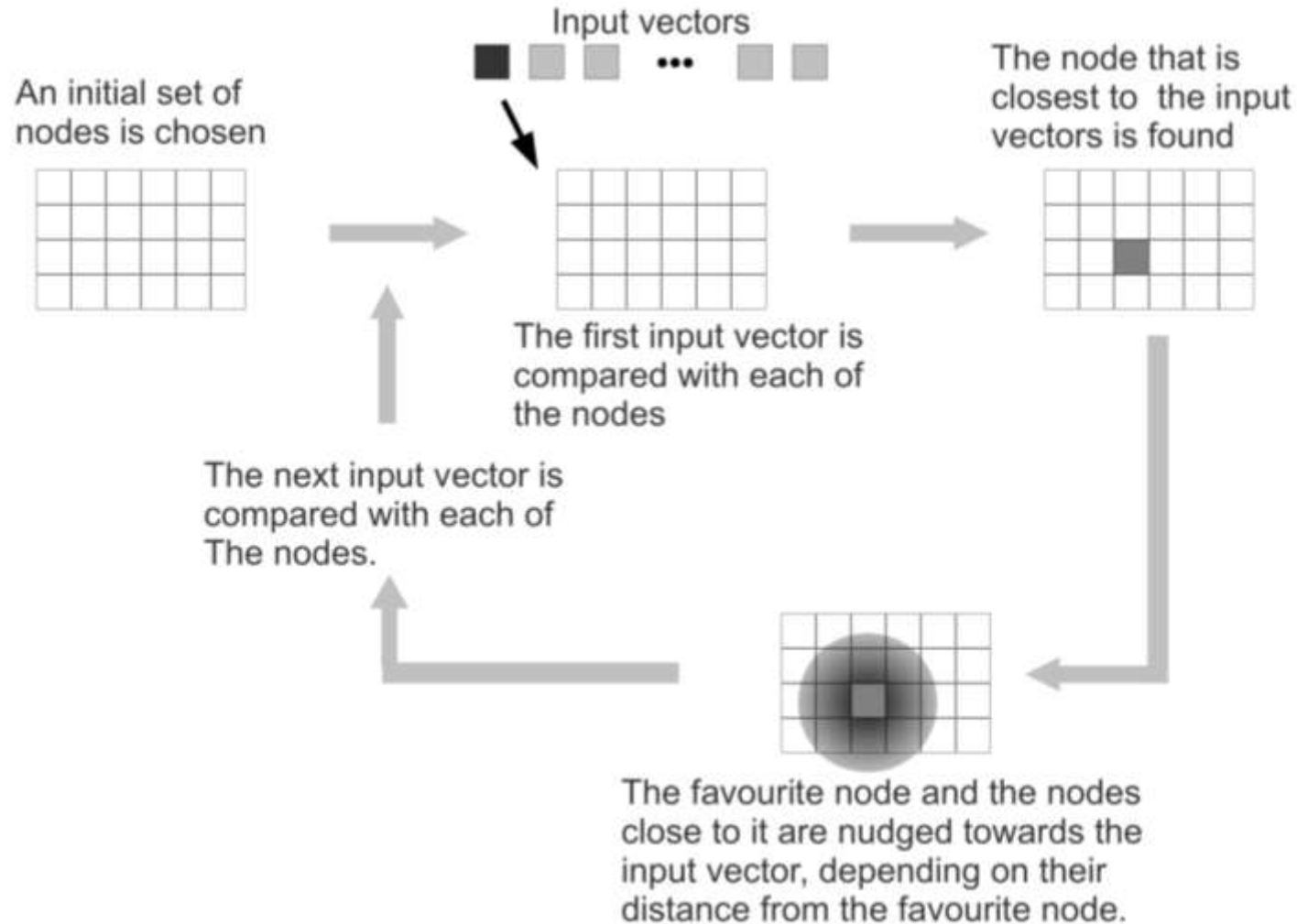


Satellite image depicting an event – open cellular structures (red circles)

# Self Organizing Maps (SOMs):

- Pattern recognition technique;
- Automatic and objective clustering analysis method which computes the multi-dimensional distribution function of any vector data.
- Previously used in:
  - **Synoptic climatological studies** (incl. wind atlas, Hagemann 2008)
  - Automatic speech recognition
  - Clinical voice analysis
  - Monitoring of the condition of industrial plants and processes
  - **Cloud classification from satellite images**
  - Analysis of electrical signals from the brain
  - Organization of and retrieval from large document collections (the WEBSOM method)
- Also known as Kohonen maps (Kohonen 2001)

# SOMs Method



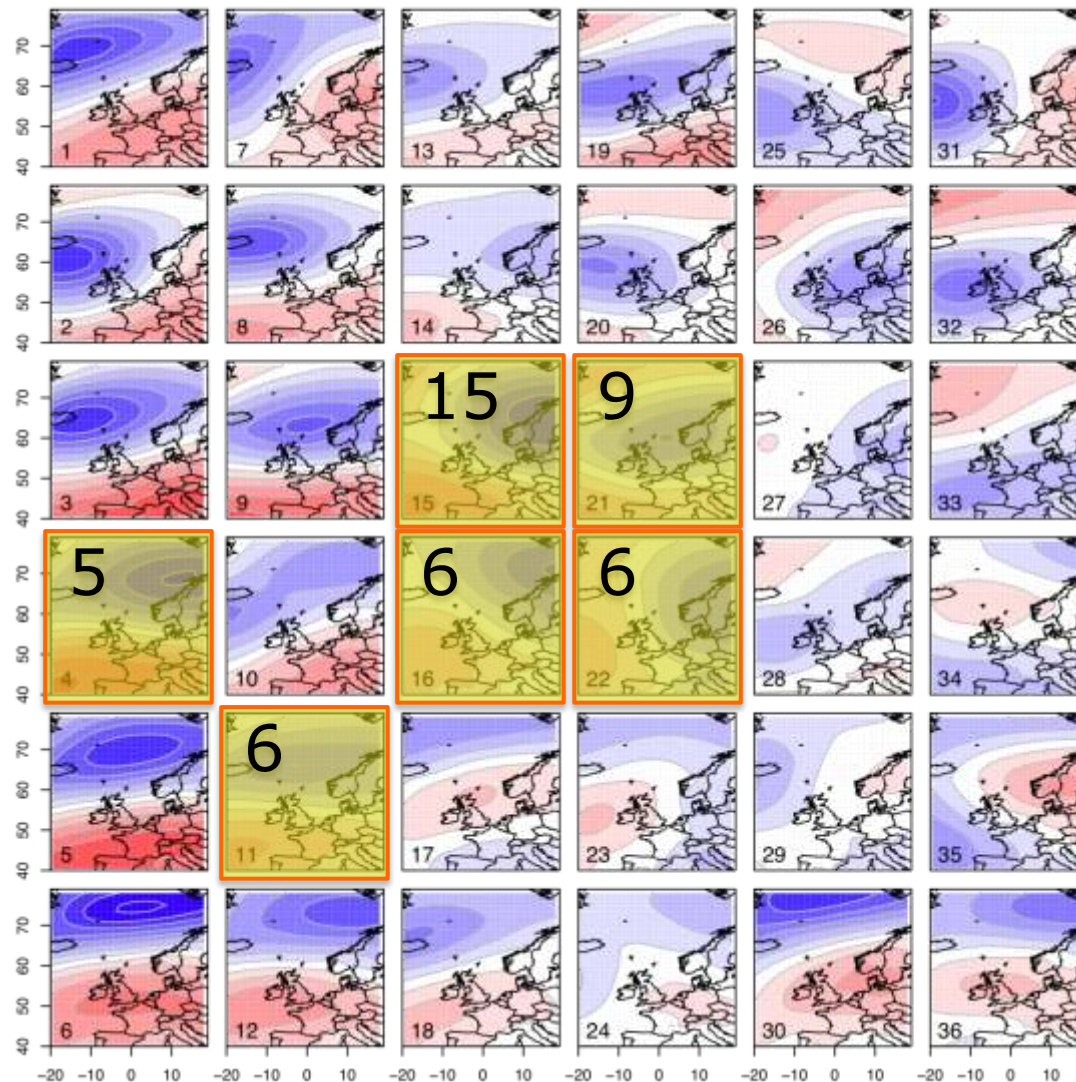
## SOMs classification

- The SOMs classification of synoptic types was based on  $1.5^\circ \times 1.5^\circ$  resolution ERA interim reanalysis MSLP data
- North Sea + Northern Europe
- daily analysis valid at 00:00 UTC
- period 1990– 2009
- *A priori* choice about the number and shape of nodes in the SOMs array
- Several algorithms exist for choosing the number of nodes
- Minimization of the *Coefficient of variation* (+ subjective choice)  
suggested topology: 6 x 6
- The synoptic patterns where are large number of extreme variability days occur are still obviously different from one another



# ERA Interim MSLP Field (6 x 6 nodes)

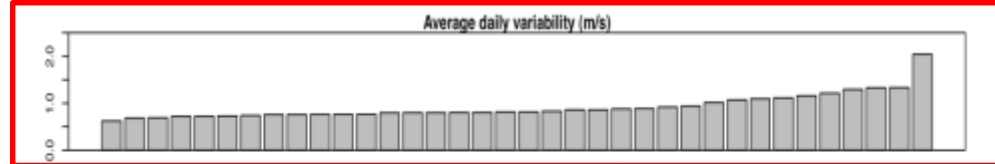
Number of  
severe  
wind  
events:  
2000-2003



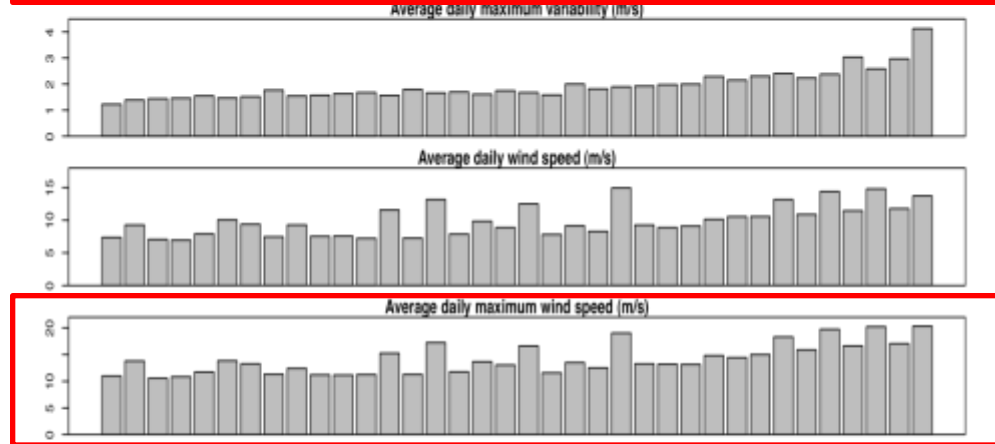
Deviation from mean pressure (hPa)



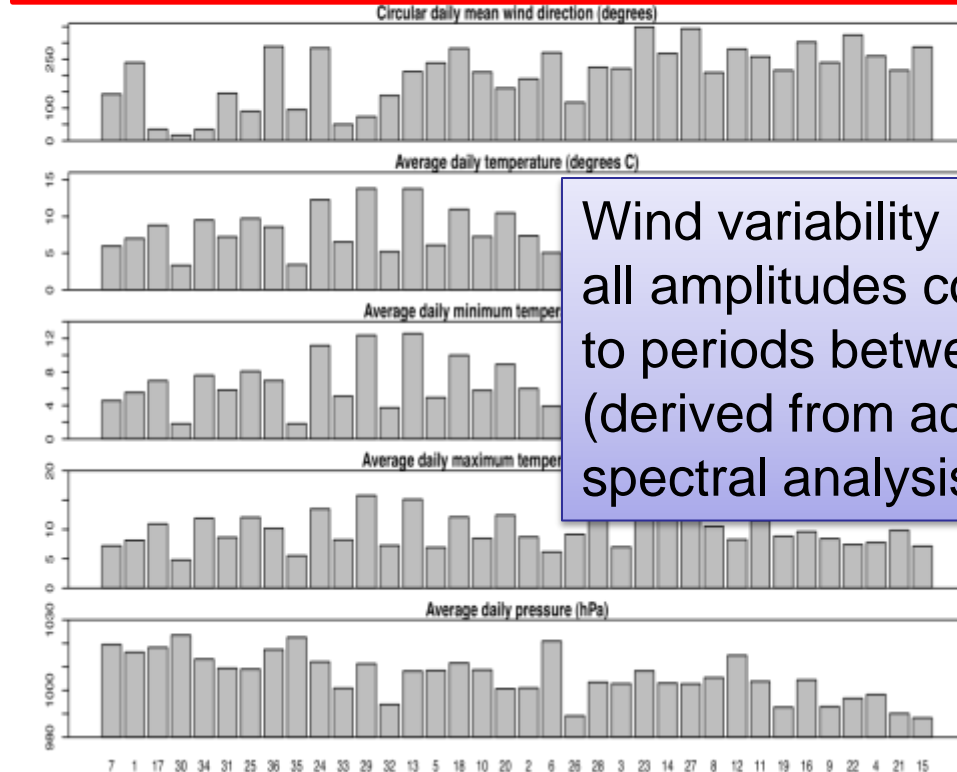
averaged daily wind  
variability (m/s)



averaged daily wind  
speed (m/s)



2000-2003: 24  
days in category  
15 → severe wind  
variability was  
observed on 63%  
of category 15  
days.

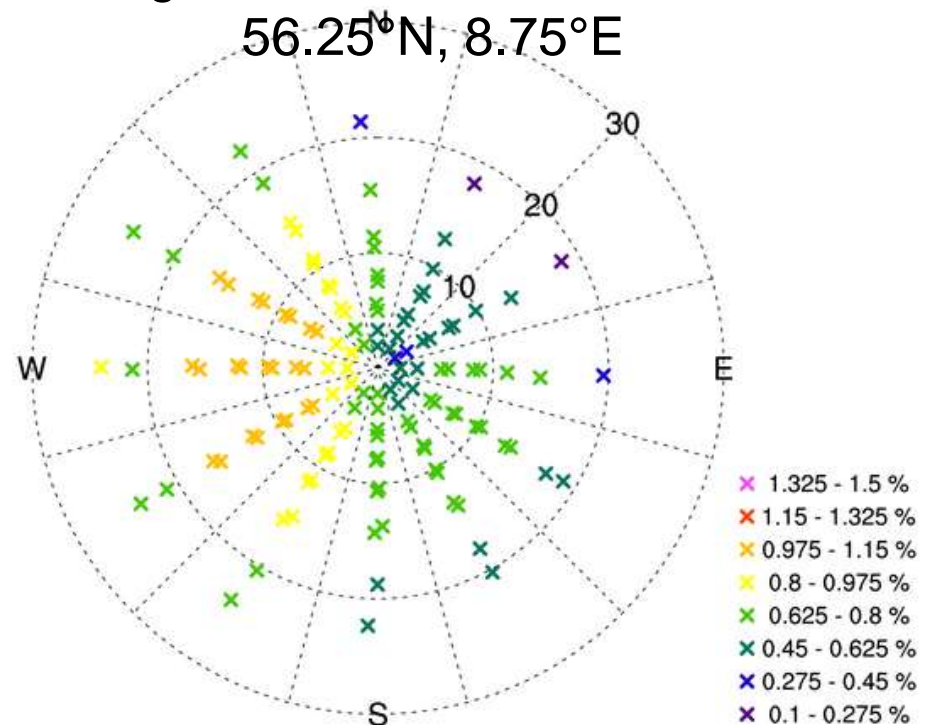


Wind variability index: sum of  
all amplitudes corresponding  
to periods between 1-3 hours  
(derived from adaptive  
spectral analysis technique)

# Comparison to Wind Class Method

- Wind classes determined from NCEP/NCAR reanalysis ( $2.5^\circ \times 2.5^\circ$ ) geostrophic winds and stability; 1990-2009 (4 times x day, 30 years)
- Local representation of the large-scale wind forcing;
- Classification used for KAMM/WAsP method – mesoscale wind atlas

Wind class frequency diagram



polar diagram

angle: wind direction

dist. origin: wind speed

color: frequency of occurrence

# Statistical models for predictability of wind variability

Categorical forecasts of wind variability: Given the predicted wind class or SOMs class, what is the probability of observing a severe wind variability 'event'?

An 'event' is defined as a day when the variability index is above the 95% percentile

Probability of Detection

Threshold	SOMS	WINDCLASS
10%	0.7	0.4
20%	0.3	0.1
30%	0.2	0.1

False alarm rate

Threshold	SOMS	WINDCLASS
10%	0.8	0.9
20%	0.5	0.8
30%	0.4	0.5

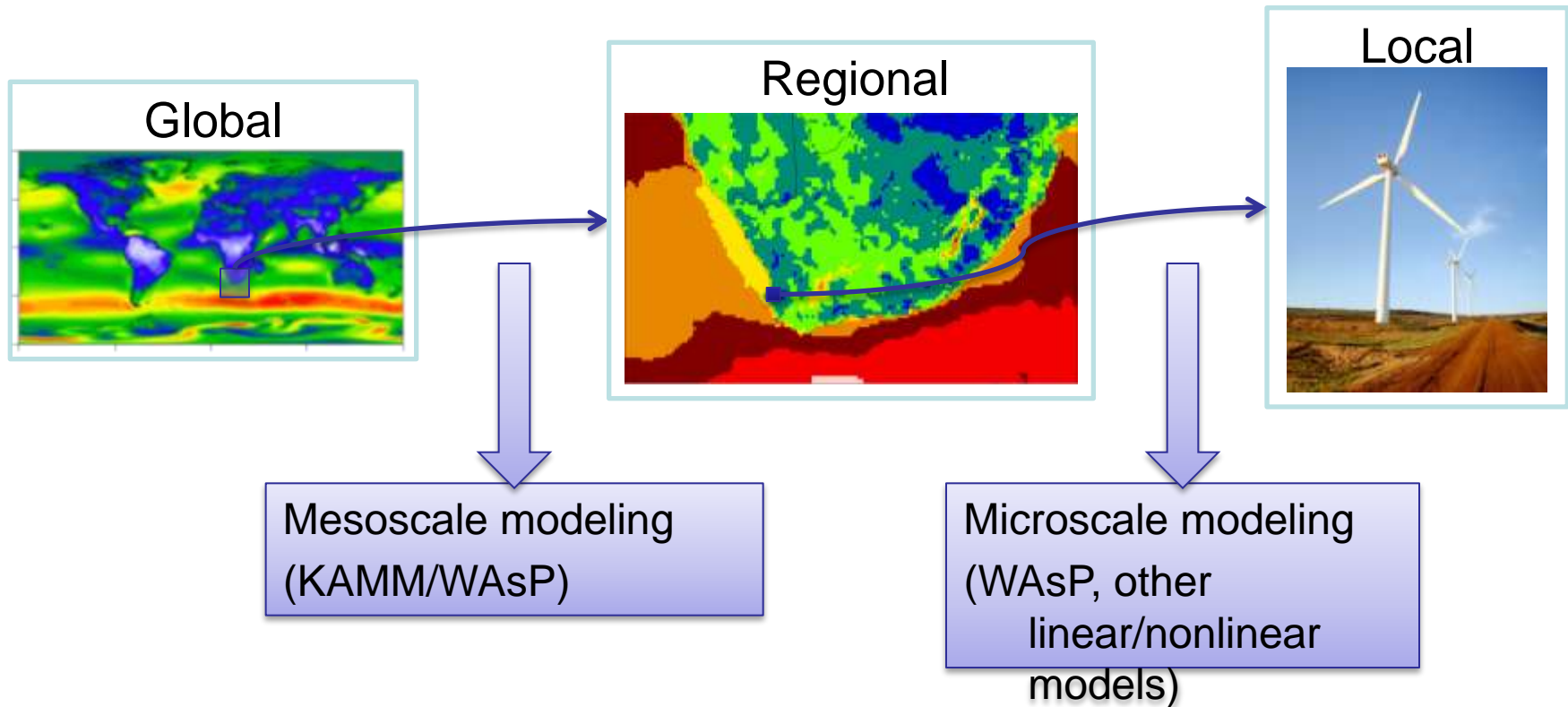
contingency SOMs

	forecast	not forecast
observed	101	48
not observed	402	2341

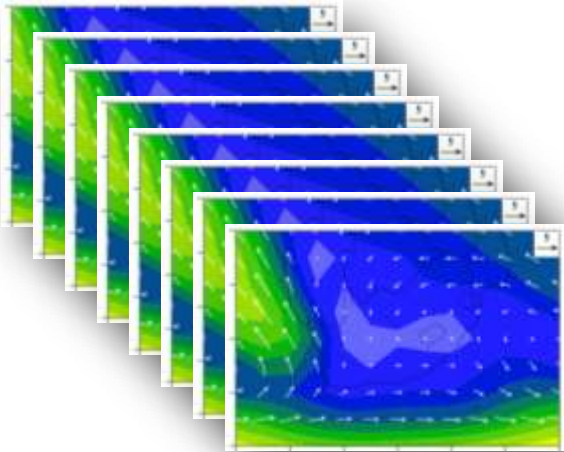
contingency wind classes

	forecast	not forecast
observed	60	89
not observed	359	2384

# Downscaling method

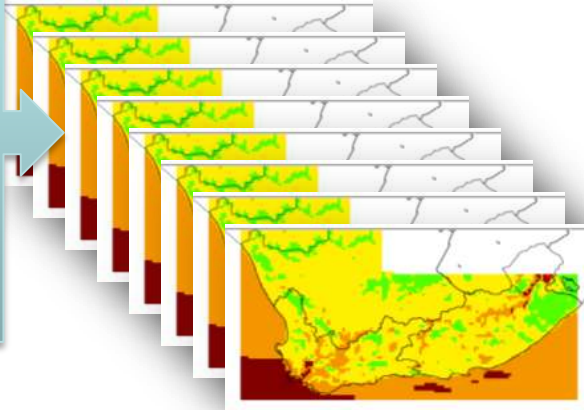


entire collection of  
large-scale atmos. conditions

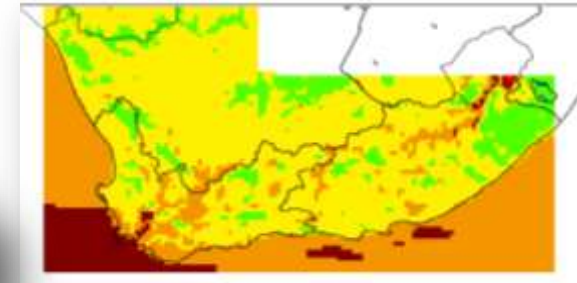


MODEL

wind maps for every  
large-scale day



wind resource map



Simple/Fast/Cheap

Complex/Slow/Expensive

Interpolation

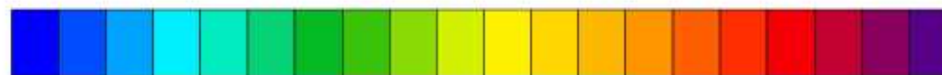
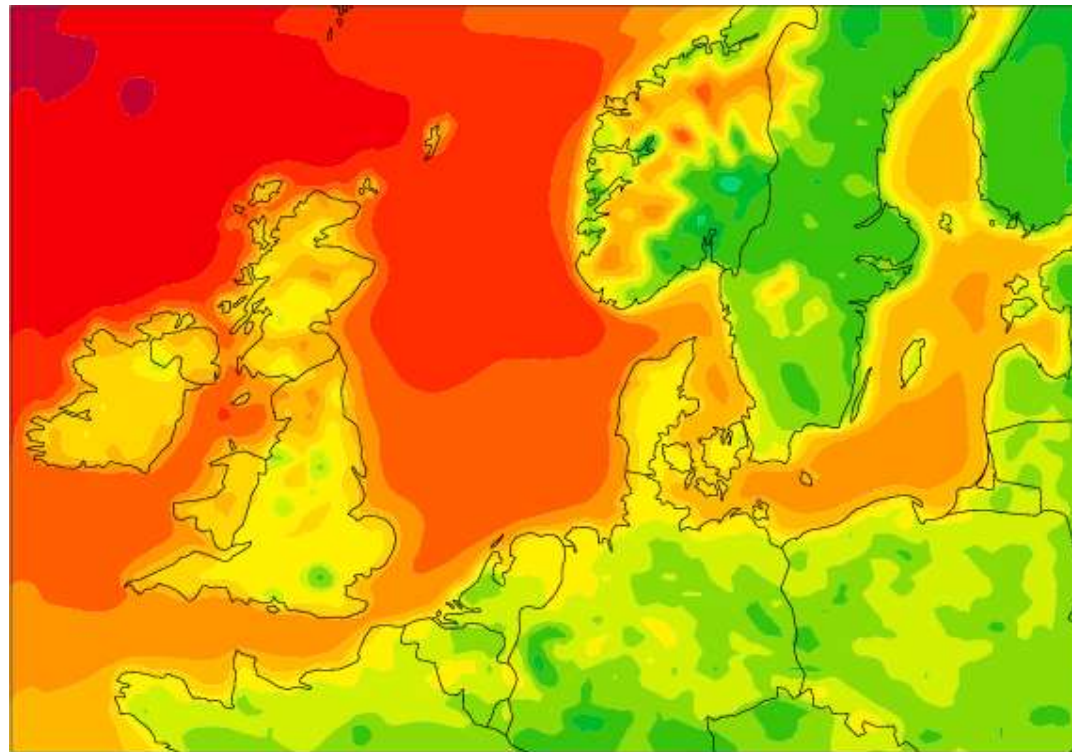
Risø Wind  
Atlas

Statistical-  
dynamical

Fully  
dynamical

# Mean wind speed (1999-2009) at 80m 15 km domain

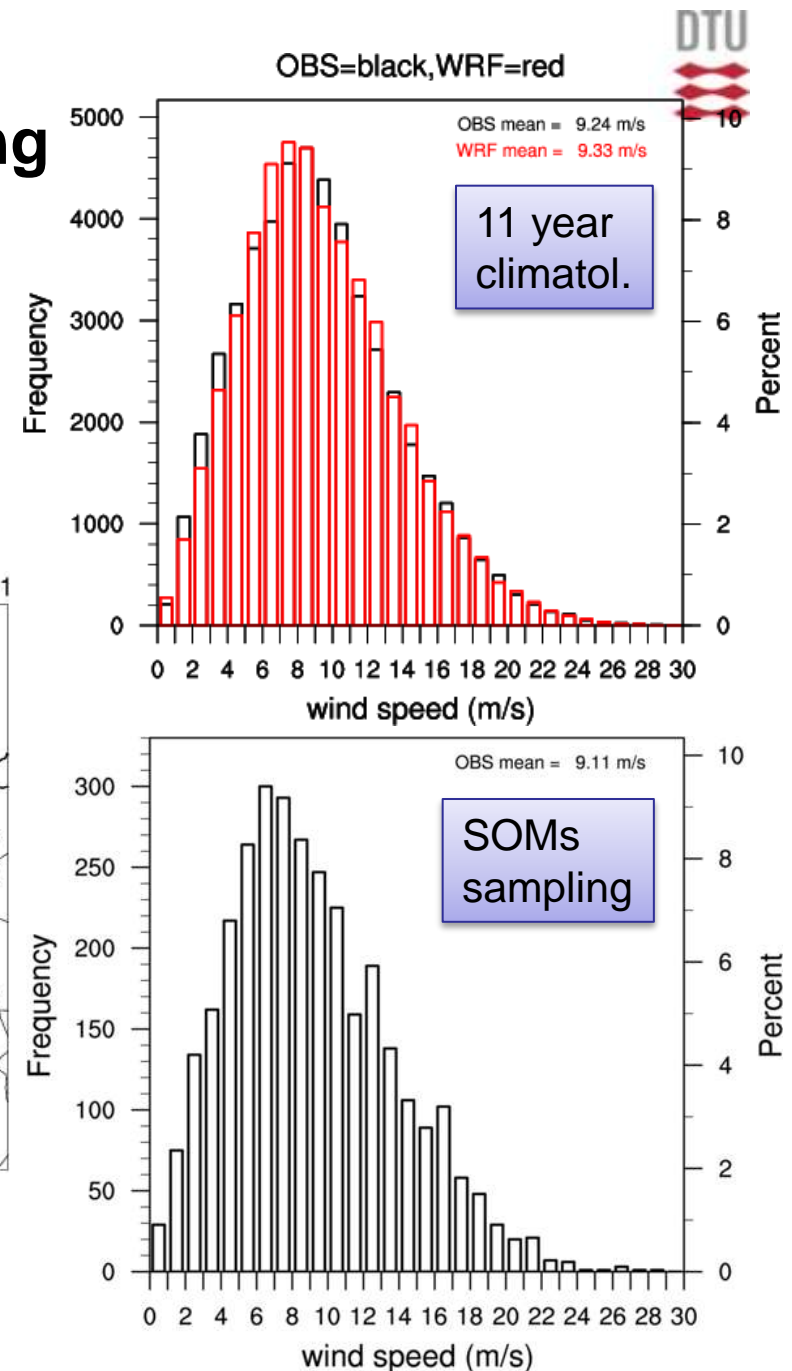
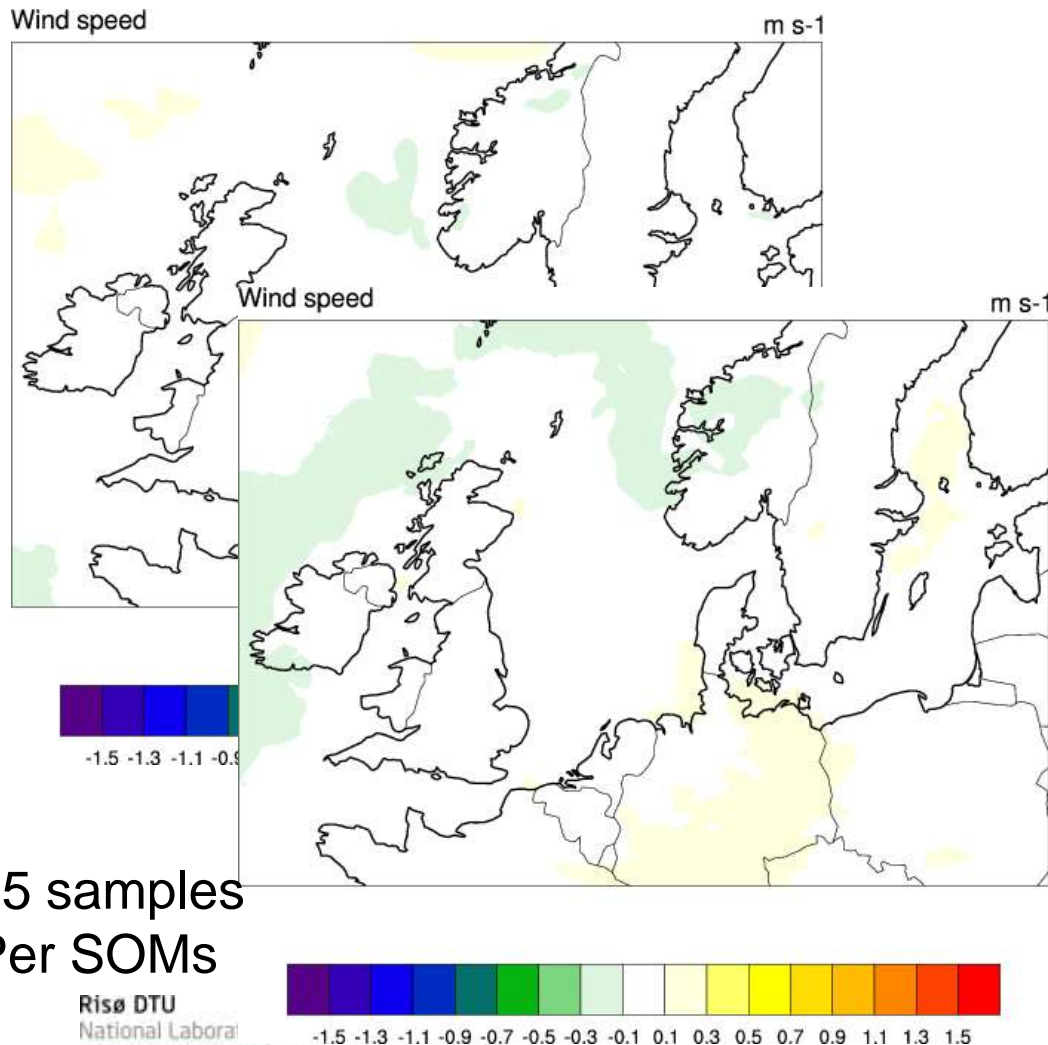
1999-2009



3 3.5 4 4.5 5 5.5 6 6.5 7 7.5 8 8.5 9 9.5 10 10.5 11 11.5 12



# Comparison of wind climate computed from various sampling techniques



## Maximum Mean Square Error in wind atlas

Number of samples	SOMs	Wind Class
4	0.60	0.24
7	0.39	0.18
15	0.24	0.12

## Concluding remarks

- Statistical model of predictability shows promising results – quite simple
- Including additional parameters (stability, sea surface temperature, etc.) should improve predictability
- Initial results show promising prospects in the use of SOMs classification of large-scale forcing to downscale mesoscale model simulations for wind resource assessment
- Several issues remain unresolved in the SOMs for mesoscale downscaling:
  - optimal number of SOMs that better describes the large-scale forcing.
    - Choosing too few SOMs is equivalent to random sampling
    - Choosing too many SOMs not seem to improve in error reduction
  - Using the internal properties of the SOMs
  - Effect on the accuracy of directional distributions and time properties (e.g. annual cycle)